

class 12

```
library(BiocManager)
library(DESeq2)

counts <- read.csv("airway_scaledcounts.csv", row.names=1)
metadata <- read.csv("airway_metadata.csv")

nrow(counts)
```

```
[1] 38694
```

```
metadata
```

	id	dex	celltype	geo_id
1	SRR1039508	control	N61311	GSM1275862
2	SRR1039509	treated	N61311	GSM1275863
3	SRR1039512	control	N052611	GSM1275866
4	SRR1039513	treated	N052611	GSM1275867
5	SRR1039516	control	N080611	GSM1275870
6	SRR1039517	treated	N080611	GSM1275871
7	SRR1039520	control	N061011	GSM1275874
8	SRR1039521	treated	N061011	GSM1275875

Q1. How many genes are in this dataset? 38694

Q2. How many 'control' cell lines do we have? 4

Q3. How would you make the above code in either approach more robust? Following the below code instead the class website code

```
#control <- metadata[metadata[, "dex"]=="control",]
#control.counts <- counts[, control$id]
#control.mean <- rowSums( control.counts )/4
#head(control.mean)
```

```
control.inds <- metadata$dex=="control"
control.ids <- metadata[control.inds, "id"]
control.counts <- counts[, control.ids]
head(control.counts)
```

	SRR1039508	SRR1039512	SRR1039516	SRR1039520
ENSG000000000003	723	904	1170	806
ENSG000000000005	0	0	0	0
ENSG000000000419	467	616	582	417
ENSG000000000457	347	364	318	330
ENSG000000000460	96	73	118	102
ENSG000000000938	0	1	2	0

```
control.mean <- rowMeans(control.counts)
head(control.mean)
```

ENSG000000000003	ENSG000000000005	ENSG000000000419	ENSG000000000457	ENSG000000000460
900.75	0.00	520.50	339.75	97.25
ENSG000000000938				
0.75				

Q4. Follow the same procedure for the treated samples (i.e. calculate the mean per gene across drug treated samples and assign to a labeled vector called treated.mean)

```
treated.inds <- metadata$dex=="treated"
treated.ids <- metadata[treated.inds, "id"]
treated.counts <- counts[, treated.ids]
head(treated.counts)
```

	SRR1039509	SRR1039513	SRR1039517	SRR1039521
ENSG000000000003	486	445	1097	604
ENSG000000000005	0	0	0	0
ENSG000000000419	523	371	781	509

ENSG000000000457	258	237	447	324
ENSG000000000460	81	66	94	74
ENSG000000000938	0	0	0	0

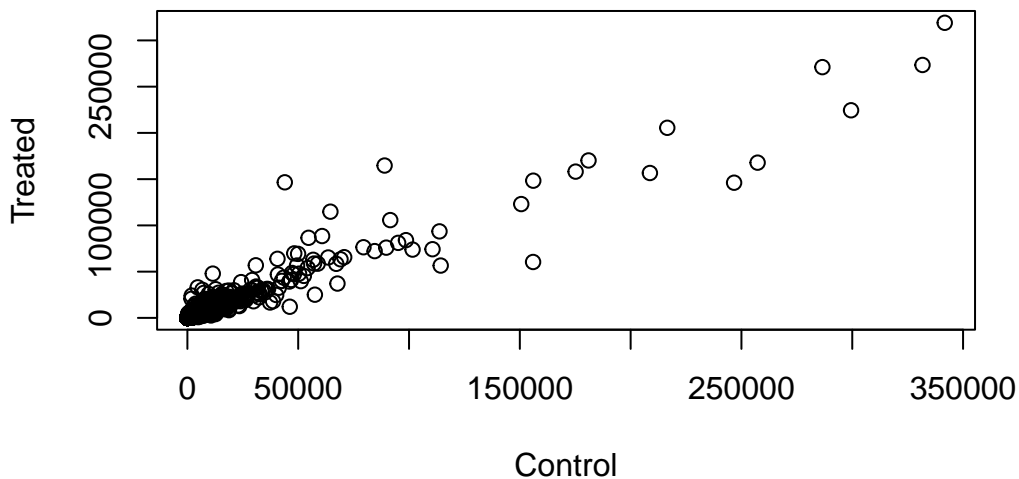
```
treated.mean <- rowMeans(treated.counts)
head(treated.mean)
```

ENSG000000000003	ENSG000000000005	ENSG000000000419	ENSG000000000457	ENSG000000000460
658.00	0.00	546.00	316.50	78.75
ENSG000000000938				
0.00				

```
meancounts <- data.frame(control.mean, treated.mean)
```

Q5 (a). Create a scatter plot showing the mean of the treated samples against the mean of the control samples. Your plot should look something like the following.

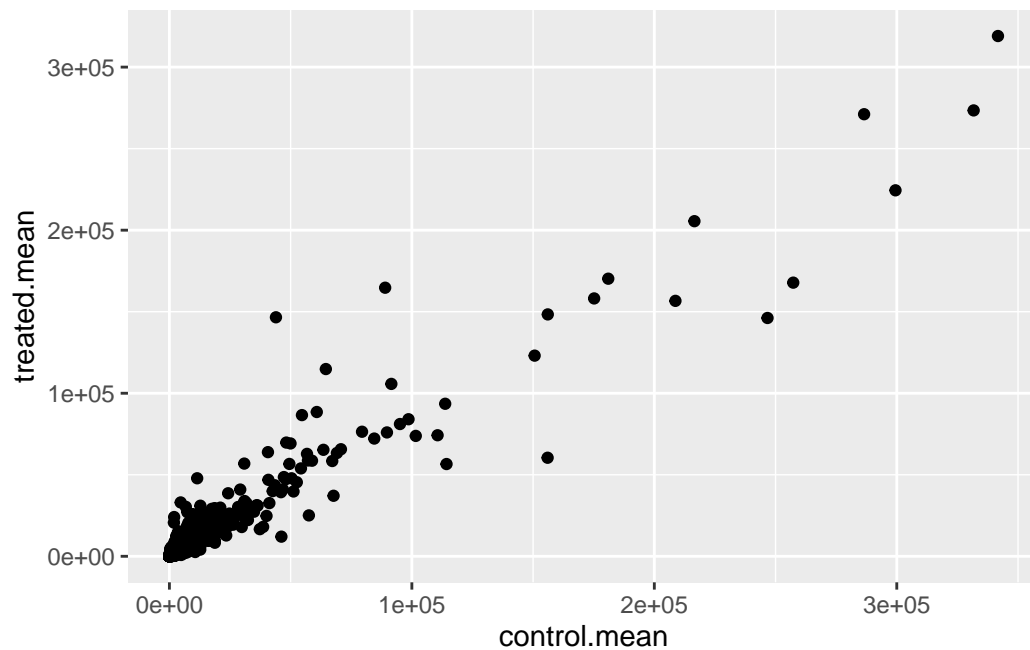
```
plot(meancounts,xlab="Control",ylab="Treated")
```



Q5 (b). You could also use the ggplot2 package to make this figure producing the plot below. What `geom_?()` function would you use for this plot? `geom_point`

```
library(ggplot2)
```

```
ggplot(meancounts)+aes(control.mean,treated.mean)+geom_point()
```

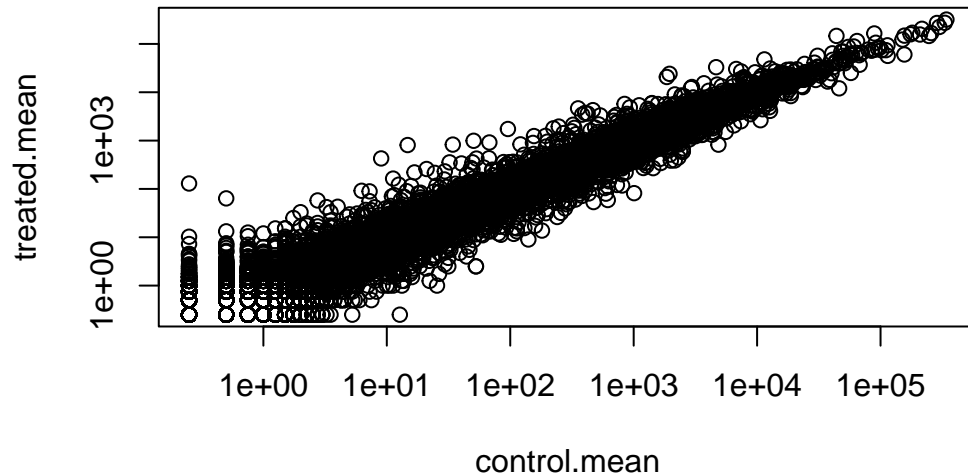


Q6. Try plotting both axes on a log scale. What is the argument to plot() that allows you to do this? log

```
plot(meancounts,log="xy")
```

Warning in xy.coords(x, y, xlabel, ylabel, log): 15032 x values <= 0 omitted from logarithmic plot

Warning in xy.coords(x, y, xlabel, ylabel, log): 15281 y values <= 0 omitted from logarithmic plot



```

meancounts$log2fc <- log2(meancounts[, "treated.mean"] / meancounts[, "control.mean"])
head(meancounts)

```

	control.mean	treated.mean	log2fc
ENSG000000000003	900.75	658.00	-0.45303916
ENSG000000000005	0.00	0.00	NaN
ENSG0000000000419	520.50	546.00	0.06900279
ENSG0000000000457	339.75	316.50	-0.10226805
ENSG0000000000460	97.25	78.75	-0.30441833
ENSG0000000000938	0.75	0.00	-Inf

Q7. What is the purpose of the `arr.ind` argument in the `which()` function call above? Why would we then take the first column of the output and need to call the `unique()` function? The `arr.ind` will cause `which()` to return all the TRUE values in both the row and column. Calling `unique()` will ensure we don't count any row twice if it has zero entries in both samples.

```

#zero.vals <- which(meancounts[,1:2]==0, arr.ind=TRUE)

#to.rm <- unique(zero.vals[,1])
#mycounts <- meancounts[-to.rm,]
#head(mycounts)

```

```

to.keep.inds <- rowSums(meancounts[,1:2] == 0) == 0
mycounts <- meancounts[to.keep.inds,]
nrow(mycounts)

```

```
[1] 21817
```

Q8. Using the up.ind vector above can you determine how many up regulated genes we have at the greater than 2 fc level? 250

Q9. Using the down.ind vector above can you determine how many down regulated genes we have at the greater than 2 fc level? 367

Q10. Do you trust these results? Why or why not? fold change can be large (e.g. »two-fold up- or down-regulation) without being statistically significant (e.g. based on p-values

```
up.ind <- mycounts$log2fc > 2
down.ind <- mycounts$log2fc < (-2)
sum(up.ind)
```

```
[1] 250
```

```
sum(down.ind)
```

```
[1] 367
```

```
sum(mycounts$log2fc >= 2)
```

```
[1] 314
```

```
library(DESeq2)
```

```
dds <- DESeqDataSetFromMatrix(countData=counts,
                              colData=metadata,
                              design=~dex)
```

converting counts to integer mode

Warning in DESeqDataSet(se, design = design, ignoreRank): some variables in design formula are characters, converting to factors

```
dds
```

```
class: DESeqDataSet
dim: 38694 8
metadata(1): version
assays(1): counts
rownames(38694): ENSG000000000003 ENSG000000000005 ... ENSG00000283120
               ENSG00000283123
rowData names(0):
colnames(8): SRR1039508 SRR1039509 ... SRR1039520 SRR1039521
colData names(4): id dex celltype geo_id
```

```
dds <- DESeq(dds)
```

estimating size factors

estimating dispersions

gene-wise dispersion estimates

mean-dispersion relationship

final dispersion estimates

fitting model and testing

```
res <- results(dds)
res <- as.data.frame(res)
#res
```

```
summary(res)
```

baseMean	log2FoldChange	lfcSE	stat
Min. : 0.0	Min. : -6.030	Min. : 0.057	Min. : -15.894
1st Qu.: 0.0	1st Qu.: -0.425	1st Qu.: 0.174	1st Qu.: -0.643
Median : 1.1	Median : -0.009	Median : 0.445	Median : -0.027
Mean : 570.2	Mean : -0.011	Mean : 1.136	Mean : 0.045
3rd Qu.: 201.8	3rd Qu.: 0.306	3rd Qu.: 1.848	3rd Qu.: 0.593
Max. : 329280.4	Max. : 8.906	Max. : 3.534	Max. : 18.422
	NA's : 13436	NA's : 13436	NA's : 13436

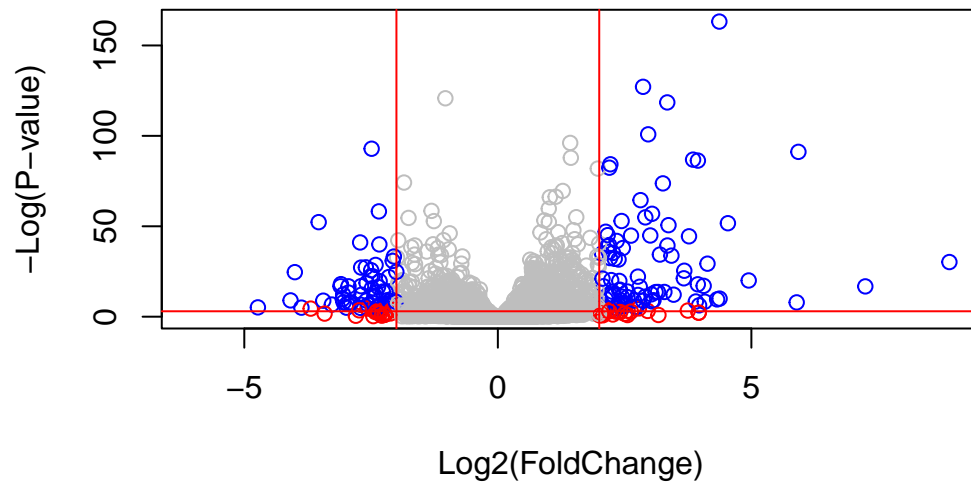
pvalue	padj
Min. : 0.000	Min. : 0.000
1st Qu.: 0.168	1st Qu.: 0.203
Median : 0.533	Median : 0.606
Mean : 0.495	Mean : 0.539
3rd Qu.: 0.800	3rd Qu.: 0.866
Max. : 1.000	Max. : 1.000
NA's : 13578	NA's : 23549

```
#plot( res$log2FoldChange, res$padj)
```

```
mycols <- rep("grey", nrow(res))
mycols[abs(res$log2FoldChange) > 2] <- "red"

inds <- (res$padj < 0.01) & (abs(res$log2FoldChange) > 2)
mycols[inds] <- "blue"

plot( res$log2FoldChange, -log(res$padj), col=mycols,
      xlab="Log2(FoldChange)",
      ylab="-Log(P-value)")
abline(v=c(-2,2), col="red")
abline(h=-log(0.05), col="red")
```

```
library("AnnotationDbi")
library("org.Hs.eg.db")
```

```
columns(org.Hs.eg.db)
```

```
[1] "ACCNUM"      "ALIAS"       "ENSEMBL"     "ENSEMBLPROT" "ENSEMBLTRANS"
[6] "ENTREZID"    "ENZYME"      "EVIDENCE"     "EVIDENCEALL"  "GENENAME"
[11] "GENETYPE"    "GO"          "GOALL"        "IPI"          "MAP"
[16] "OMIM"        "ONTOLOGY"    "ONTOLOGYALL" "PATH"         "PFAM"
[21] "PMID"        "PROSITE"     "REFSEQ"       "SYMBOL"       "UCSCKG"
[26] "UNIPROT"
```

```
res$symbol <- mapIds(org.Hs.eg.db,
  keys=row.names(res),
  keytype="ENSEMBL",
  column="SYMBOL",
  multiVals="first")
```

'select()' returned 1:many mapping between keys and columns

```
res$entrez <- mapIds(org.Hs.eg.db,
  keys=row.names(res),
  keytype="ENSEMBL",
  column="ENTREZID",
  multiVals="first")
```

'select()' returned 1:many mapping between keys and columns

```
res$genename <- mapIds(org.Hs.eg.db,
  keys=row.names(res),
  keytype="ENSEMBL",
  column="GENENAME",
  multiVals="first")
```

'select()' returned 1:many mapping between keys and columns

```
head(res)
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue
ENSG000000000003	747.1941954	-0.35070302	0.1682457	-2.0844697	0.03711747
ENSG000000000005	0.0000000	NA	NA	NA	NA
ENSG000000000419	520.1341601	0.20610777	0.1010592	2.0394752	0.04140263
ENSG000000000457	322.6648439	0.02452695	0.1451451	0.1689823	0.86581056
ENSG000000000460	87.6826252	-0.14714205	0.2570073	-0.5725210	0.56696907
ENSG000000000938	0.3191666	-1.73228897	3.4936010	-0.4958463	0.62000288

	padj	symbol	entrez
ENSG000000000003	0.1630348	TSPAN6	7105
ENSG000000000005	NA	TNMD	64102
ENSG000000000419	0.1760317	DPM1	8813
ENSG000000000457	0.9616942	SCYL3	57147
ENSG000000000460	0.8158486	C1orf112	55732
ENSG000000000938	NA	FGR	2268

	genename
ENSG000000000003	tetraspanin 6
ENSG000000000005	tenomodulin
ENSG000000000419	dolichyl-phosphate mannosyltransferase subunit 1, catalytic
ENSG000000000457	SCY1 like pseudokinase 3
ENSG000000000460	chromosome 1 open reading frame 112
ENSG000000000938	FGR proto-oncogene, Src family tyrosine kinase

```
library(pathview)
```

```
#####  
Pathview is an open source software package distributed under GNU General  
Public License version 3 (GPLv3). Details of GPLv3 is available at  
http://www.gnu.org/licenses/gpl-3.0.html. Particullary, users are required to  
formally cite the original Pathview paper (not just mention it) in publications  
or products. For details, do citation("pathview") within R.
```

The pathview downloads and uses KEGG data. Non-academic uses may require a KEGG
license agreement (details at <http://www.kegg.jp/kegg/legal.html>).

```
#####
```

```
library(gage)
```

```
library(gageData)
```

```
data(kegg.sets.hs)  
data(sigmet.idx.hs)
```

```
kegg.sets.hs = kegg.sets.hs[sigmet.idx.hs]  
head(kegg.sets.hs)
```

```
$`hsa00232 Caffeine metabolism`  
[1] "10" "1544" "1548" "1549" "1553" "7498" "9"
```

```
$`hsa00983 Drug metabolism - other enzymes`  
[1] "10" "1066" "10720" "10941" "151531" "1548" "1549" "1551"  
[9] "1553" "1576" "1577" "1806" "1807" "1890" "221223" "2990"  
[17] "3251" "3614" "3615" "3704" "51733" "54490" "54575" "54576"  
[25] "54577" "54578" "54579" "54600" "54657" "54658" "54659" "54963"  
[33] "574537" "64816" "7083" "7084" "7172" "7363" "7364" "7365"  
[41] "7366" "7367" "7371" "7372" "7378" "7498" "79799" "83549"  
[49] "8824" "8833" "9" "978"
```

\$`hsa00230 Purine metabolism`

[1]	"100"	"10201"	"10606"	"10621"	"10622"	"10623"	"107"	"10714"
[9]	"108"	"10846"	"109"	"111"	"11128"	"11164"	"112"	"113"
[17]	"114"	"115"	"122481"	"122622"	"124583"	"132"	"158"	"159"
[25]	"1633"	"171568"	"1716"	"196883"	"203"	"204"	"205"	"221823"
[33]	"2272"	"22978"	"23649"	"246721"	"25885"	"2618"	"26289"	"270"
[41]	"271"	"27115"	"272"	"2766"	"2977"	"2982"	"2983"	"2984"
[49]	"2986"	"2987"	"29922"	"3000"	"30833"	"30834"	"318"	"3251"
[57]	"353"	"3614"	"3615"	"3704"	"377841"	"471"	"4830"	"4831"
[65]	"4832"	"4833"	"4860"	"4881"	"4882"	"4907"	"50484"	"50940"
[73]	"51082"	"51251"	"51292"	"5136"	"5137"	"5138"	"5139"	"5140"
[81]	"5141"	"5142"	"5143"	"5144"	"5145"	"5146"	"5147"	"5148"
[89]	"5149"	"5150"	"5151"	"5152"	"5153"	"5158"	"5167"	"5169"
[97]	"51728"	"5198"	"5236"	"5313"	"5315"	"53343"	"54107"	"5422"
[105]	"5424"	"5425"	"5426"	"5427"	"5430"	"5431"	"5432"	"5433"
[113]	"5434"	"5435"	"5436"	"5437"	"5438"	"5439"	"5440"	"5441"
[121]	"5471"	"548644"	"55276"	"5557"	"5558"	"55703"	"55811"	"55821"
[129]	"5631"	"5634"	"56655"	"56953"	"56985"	"57804"	"58497"	"6240"
[137]	"6241"	"64425"	"646625"	"654364"	"661"	"7498"	"8382"	"84172"
[145]	"84265"	"84284"	"84618"	"8622"	"8654"	"87178"	"8833"	"9060"
[153]	"9061"	"93034"	"953"	"9533"	"954"	"955"	"956"	"957"
[161]	"9583"	"9615"						

\$`hsa04514 Cell adhesion molecules (CAMs)`

[1]	"1000"	"1001"	"100133583"	"1002"	"1003"	"100506658"
[7]	"1013"	"10666"	"10686"	"1272"	"1364"	"1365"
[13]	"1366"	"137075"	"1462"	"1493"	"149461"	"214"
[19]	"22871"	"23114"	"23308"	"23562"	"23705"	"24146"
[25]	"257194"	"25945"	"26047"	"26285"	"2734"	"29126"
[31]	"29851"	"3105"	"3106"	"3107"	"3108"	"3109"
[37]	"3111"	"3112"	"3113"	"3115"	"3117"	"3118"
[43]	"3119"	"3122"	"3123"	"3125"	"3126"	"3127"
[49]	"3133"	"3134"	"3135"	"3383"	"3384"	"3385"
[55]	"3655"	"3676"	"3680"	"3683"	"3684"	"3685"
[61]	"3688"	"3689"	"3695"	"3696"	"3897"	"4099"
[67]	"4267"	"4359"	"4684"	"4685"	"4756"	"4897"
[73]	"4950"	"49861"	"5010"	"50848"	"51208"	"5133"
[79]	"5175"	"53842"	"54413"	"57502"	"57555"	"57863"
[85]	"5788"	"5792"	"5797"	"5817"	"5818"	"5819"
[91]	"58494"	"6382"	"6383"	"6385"	"6401"	"6402"
[97]	"6403"	"6404"	"652614"	"6614"	"6693"	"6900"
[103]	"7122"	"7412"	"80380"	"80381"	"8174"	"83700"
[109]	"8506"	"8516"	"9019"	"9071"	"9073"	"9074"

[115]	"9075"	"9076"	"9080"	"90952"	"914"	"920"
[121]	"923"	"925"	"926"	"933"	"9369"	"9378"
[127]	"9379"	"940"	"941"	"942"	"947"	"958"
[133]	"959"	"965"	"9672"	"999"		

\$`hsa04010 MAPK signaling pathway`

[1]	"10000"	"100137049"	"10125"	"10235"	"10368"	"10369"
[7]	"10454"	"10746"	"10912"	"11072"	"11184"	"11221"
[13]	"11261"	"1147"	"115727"	"123745"	"1326"	"1386"
[19]	"1398"	"1399"	"1432"	"1616"	"1647"	"1649"
[25]	"1843"	"1844"	"1845"	"1846"	"1847"	"1848"
[31]	"1849"	"1850"	"1852"	"1950"	"1956"	"2002"
[37]	"2005"	"207"	"208"	"2122"	"2246"	"2247"
[43]	"2248"	"2249"	"2250"	"2251"	"2252"	"2253"
[49]	"2254"	"2255"	"2256"	"2257"	"2258"	"2259"
[55]	"2260"	"2261"	"2263"	"2264"	"22800"	"22808"
[61]	"23118"	"2316"	"23162"	"2317"	"2318"	"2353"
[67]	"23542"	"25780"	"26279"	"26281"	"26291"	"27006"
[73]	"27091"	"27092"	"27330"	"2768"	"2872"	"2885"
[79]	"30814"	"3164"	"3265"	"3303"	"3304"	"3305"
[85]	"3306"	"3310"	"3312"	"3315"	"355"	"3551"
[91]	"3552"	"3553"	"3554"	"356"	"3725"	"3727"
[97]	"3845"	"391013"	"3925"	"408"	"409"	"4137"
[103]	"4149"	"4208"	"4214"	"4215"	"4216"	"4217"
[109]	"4296"	"4342"	"4609"	"4616"	"468"	"4763"
[115]	"4773"	"4776"	"4790"	"4791"	"4803"	"4893"
[121]	"4908"	"4909"	"4914"	"4915"	"50487"	"5058"
[127]	"5062"	"51295"	"51347"	"5154"	"5155"	"5156"
[133]	"5159"	"51701"	"51776"	"5319"	"5320"	"5321"
[139]	"5322"	"5494"	"5495"	"5530"	"5532"	"5533"
[145]	"5534"	"5535"	"5536"	"5566"	"5567"	"5568"
[151]	"5578"	"5579"	"55799"	"5582"	"5594"	"5595"
[157]	"55970"	"5598"	"5599"	"5600"	"5601"	"5602"
[163]	"5603"	"5604"	"5605"	"5606"	"5607"	"5608"
[169]	"5609"	"5613"	"56940"	"57551"	"5778"	"5801"
[175]	"5871"	"5879"	"5880"	"5881"	"5894"	"5906"
[181]	"5908"	"5921"	"5922"	"5923"	"5924"	"59283"
[187]	"59284"	"59285"	"5970"	"5971"	"6195"	"6196"
[193]	"6197"	"6237"	"627"	"6300"	"63928"	"6416"
[199]	"64600"	"6654"	"6655"	"6722"	"673"	"6788"
[205]	"6789"	"6885"	"7040"	"7042"	"7043"	"7046"
[211]	"7048"	"7124"	"7132"	"7157"	"7186"	"7189"
[217]	"773"	"774"	"775"	"776"	"777"	"778"

```
[223] "7786"      "779"      "781"      "782"      "783"      "784"
[229] "785"      "7850"     "786"      "7867"     "8074"     "80824"
[235] "81579"    "836"      "8398"     "8399"     "84647"    "84867"
[241] "8491"    "8517"     "8550"     "8569"     "8649"     "8681"
[247] "8817"    "8822"     "8823"     "8911"     "8912"     "8913"
[253] "8986"    "9020"     "9064"     "9175"     "9252"     "9254"
[259] "9261"    "929"      "9344"     "93589"    "9448"     "9479"
[265] "9693"    "994"      "9965"     "998"
```

```
$`hsa04012 ErbB signaling pathway`
```

```
[1] "10000" "1026"  "1027"  "10298" "10718" "1398"  "1399"  "145957"
[9] "1839"  "1950"  "1956"  "1978"  "2002"  "2064"  "2065"  "2066"
[17] "2069"  "207"   "208"   "23533" "23624" "2475"  "25"    "2549"
[25] "25759" "27"    "2885"  "2932"  "3084"  "3265"  "369"   "3725"
[33] "374"   "3845"  "399694" "4609"  "4690"  "4893"  "5058"  "5062"
[41] "5063"  "5290"  "5291"  "5293"  "5294"  "5295"  "5296"  "5335"
[49] "53358" "5336"  "5578"  "5579"  "5582"  "5594"  "5595"  "5599"
[57] "5601"  "5602"  "5604"  "5605"  "5609"  "56924" "57144" "572"
[65] "5747"  "5894"  "6198"  "6199"  "6416"  "6464"  "6654"  "6655"
[73] "6714"  "673"   "6776"  "6777"  "685"   "7039"  "815"   "816"
[81] "817"   "818"   "8440"  "8503"  "867"   "868"   "9542"
```

```
foldchanges = res$log2FoldChange
names(foldchanges) = res$entrez
head(foldchanges)
```

```
          7105          64102          8813          57147          55732          2268
-0.35070302          NA  0.20610777  0.02452695 -0.14714205 -1.73228897
```

```
keggres = gage(foldchanges, gsets=kegg.sets.hs)
attributes(keggres)
```

```
$names
[1] "greater" "less"    "stats"
```

```
head(keggres$less,5)
```

	p.geomean	stat.mean
hsa04672 Intestinal immune network for IgA production	0.006043452	-2.560547
hsa04340 Hedgehog signaling pathway	0.013323955	-2.248547
hsa04916 Melanogenesis	0.030996739	-1.877209
hsa04972 Pancreatic secretion	0.037135109	-1.794718
hsa04612 Antigen processing and presentation	0.044082096	-1.716738

	p.val	q.val
hsa04672 Intestinal immune network for IgA production	0.006043452	0.9763115
hsa04340 Hedgehog signaling pathway	0.013323955	0.9763115
hsa04916 Melanogenesis	0.030996739	0.9763115
hsa04972 Pancreatic secretion	0.037135109	0.9763115
hsa04612 Antigen processing and presentation	0.044082096	0.9763115

	set.size	exp1
hsa04672 Intestinal immune network for IgA production	47	0.006043452
hsa04340 Hedgehog signaling pathway	56	0.013323955
hsa04916 Melanogenesis	101	0.030996739
hsa04972 Pancreatic secretion	101	0.037135109
hsa04612 Antigen processing and presentation	75	0.044082096

```
pathview(gene.data=foldchanges, pathway.id="hsa05310")
```

'select()' returned 1:1 mapping between keys and columns

Info: Working in directory /Users/chrisz/Desktop/BGGN 213/week 6/class12

Info: Writing image file hsa05310.pathview.png

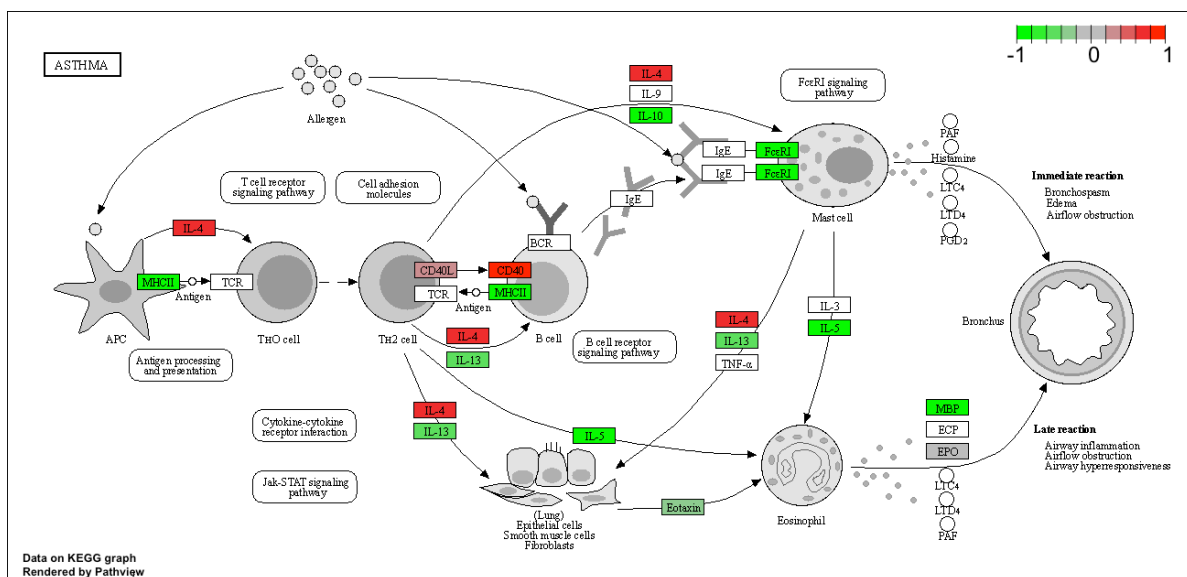


Figure 1: The asthma pathway with hsa05310 gene